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Abstract

We study the consequences of unobserved heterogeneity when employing different econometric methods in the estimation of two major value-relevance models: the Price Regression Model (PRM) and the Return Regression Model (RRM). Leveraging a large panel data set of European listed companies, we first demonstrate that robust Hausman tests and Breusch-Pagan Lagrange Multiplier tests are of fundamental importance to choose correctly among a fixed-effects model, a random-effects model, or a pooled OLS model. Second, we provide evidence that replacing firm fixed-effects with country and industry fixed-effects can lead to large differences in the magnitude of the key coefficients, with serious consequences for the interpretation of the effect of changes in earnings and book values per share on firm value. Finally, we offer recommendations to applied researchers aiming to improve the robustness of their econometric strategy.

Keywords: *Value-Relevance; Linear Information Model; IFRS; Price Regression Model; Return Regression Model*; *Panel Data.*

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Abstract

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Keywords: *Value-Relevance; Linear Information Model; IFRS; Price Regression Model; Return Regression Model*; *Panel Data.*

1. Introduction

We investigate whether unobserved heterogeneity can lead to misspecifications in the estimation of value-relevance models. This is an important topic in other related fields such as asset pricing and corporate finance, as recently documented by Gormley and Matsa (2014). However, the value-relevance accounting literature has hitherto only partially investigated this issue.

Value-relevance studies aim to assess the extent to which accounting data reflect information that is "relevant" for firm value as represented by the stock price (Holthausen and Watts, 2001). Over the last decades, a substantial amount of accounting studies have focused on the value relevance effects around the implementation of International Financial Reporting Standards, henceforth IFRS (Callao et al., 2007; Zeff, 2007; Aharony et al., 2010; Devalle et al., 2010; Horton and Serafeim, 2010; Barth et al., 2012; Tsalavoutas et al., 2012; Barth et al., 2014; Christensen et al., 2015).

The motivation of our study lies in the heterogeneity of the approaches employed in the empirical literature, which hinders the comparability of findings for different countries (ICAEW, 2014). To address this issue and to answer calls for more robust econometric analysis in accounting research (Brüggemann et al, 2013), we investigate the impact of using different approaches on the magnitude and statistical significance of the coefficients of regression models typically employed in value relevance studies.

The validity of the coefficient estimates of value-relevance models is a key topic in the value-relevance literature (Kothari and Zimmerman, 1995; Barth and Kallapur, 1996; Aboody et al., 2002). However, the existing literature does not provide clear guidelines to applied researchers on how to choose among different types of econometric approaches. It is also unclear whether choosing an inappropriate model may lead to wrong inferences with respect to whether a certain accounting variable is value relevant or not. This is the focus of our study.

Our contribution to the literature is threefold. First, we demonstrate the importance of employing the Hausman test (in its robust version, as developed by Arellano, 1993, and Wooldridge, 2002, and

2010) to decide whether a Fixed Effects (FE) model or a Random Effects (RE) model should be used. While some papers have used the Hausman test to select the correct model between FE and RE model (for example, Worthington and West, 2004), they tend not to use the "robust" Hausman test, and in most cases (for example, Devalle et al., 2010) neither version of the Hausman test is employed. For cases where the RE model is valid, we point out that the Breusch-Pagan Lagrange Multiplier (LM) test should be run to choose between the OLS model and the RE model. Using these tests is important to ensure that the estimator chosen is consistent and efficient. In particular, choosing the FE model when the RE model should be preferred may lead to insignificant coefficients, because the RE model is more efficient than the FE model. This is a crucial issue for researchers interested in value relevance analysis because an insignificant coefficient indicates that a variable is *not* value relevant.

Second, we investigate the differential impact of firm FE, year FE, country FE, and industry FE. A recent study by Amir et al. (2016) points out that many empirical accounting researchers tend to (incorrectly) replace firm FE with other forms of FE, in particular industry FE. Amir et al. (2016) address this issue only for U.S. listed firms (which prepare their financial statements according to the U.S. GAAP), and they do not focus on value relevance models. We extend their findings in three ways: i) we examine value relevance models; ii) we use data for European listed firms for the period of compulsory IFRS adoption (2005 onwards); and iii) we examine the impact of the length of the sample period on the bias resulting from neglecting firm FE using Monte Carlo simulations.

Third, we examine whether using different levels of clustering the standard errors leads to substantially different results, and we check for the potential impact of attrition. We provide evidence that clustering the standard errors matters, and we emphasise the impact of using a small number of clusters on the extent of the bias. Attrition bias may also affect the coefficient estimates and overall explanatory power of the model, and this problem is likely to be more acute for sample periods including the 2008-2009 crisis.

The structure of the rest of the paper is as follows. Section 2 describes the sample composition and data. Section 3 examines the impact of model specification on a sample of European listed firms. Section 4 concludes the paper and offers recommendations for future research.

2. Sample and data

For our empirical analysis, we focus on two models widely employed in the value relevance literature: the Price Regression Model (PRM) and the Return Regression Model (RRM). These models constitute the basis to examine the value relevance of book value of equity and earnings, as well as specific items of financial statements, such as research and development expenditure (Aboody and Lev, 1998; Kallapur and Kwan, 2004).[1]

The PRM involves estimating a regression of stock price (P) on book value ($BVPS$) and earnings (EPS) per share (Barth et al., 2008):[2]

$$P_{it} = a + bBVPS_{it} + cEPS_{it} + e_{it} \qquad \text{(Eq. 1)}$$

where $i = 1, 2, ..., N$ represent firms, $t = 1, 2, \ldots, T$ represent years.

The RRM is based on a regression of stock returns on earnings per share and changes in earnings per share:

$$RET_{it} = a + bEPS_{it} / P_{it-1} + c\Delta EPS_{it} / P_{it-1} + e_{it} \qquad \text{(Eq. 2)}$$

where $RET_{it} = \dfrac{P_{it} + DPS_{it} - P_{it-1}}{P_{it-1}}$ and $\Delta EPS_{it} = EPS_{it} - EPS_{it-1}$ (Barth and Clinch, 2009).

[1] These models have also been the focus of similar papers that have examined methodological issues in value relevance models, such as Barth and Clinch (2009), who evaluate the possibility of omitted variables bias in the PRM and RRM, and the importance of scale effects.

[2] We focus on this model, which is based on per-share values, because it is less likely to be prone to scale effects than models based on the market value of equity, book value of equity, and earnings. Some studies also use market value of equity, book value of equity, and earnings, rather than the per share figures, and in certain cases the variables are adjusted for scale effects through a common deflator. For an explanation of the consequences of using different specifications and deflators, see Barth and Clinch (2009).

Where P is the stock price as at six months after fiscal year-end (Lang et al., 2006; Barth et al., 2008) and DPS denotes dividends per share. For simplicity, in the discussion below we use the notation $DEPS = (EPS_{it} / P_{it-1})$ and $\Delta DEPS = (\Delta EPS_{it} / P_{it-1})$. All variables are winsorised at the 1st and 99th percentile to reduce the potential impact of outliers.

We collect accounting data for sample of European listed companies from *Amadeus* for 71 industries,[3] selected on the basis of the first two digits of the U.S. SIC code,[4] and 17 European countries. Price data are collected from *Datastream.* We choose to examine European listed firms because the majority of the recent value-relevance studies have focused on Europe, especially to assess the impact of IFRS reporting on value relevance (Devalle et al., 2010; Barth et al., 2014). The cross-country nature of our sample enables us test the robustness of our analysis across different institutional, regulatory and cultural settings (McLeay and Jafaar, 2007; Christensen et al., 2013a, 2013b; Veith and Werner, 2014).

We choose 2005 as the beginning of our sample period because prior to 2005 even listed firms could use domestic GAAP and this may produce some noise in the data. We choose 2013 as final year because most of the papers on IFRS focus on sample periods shorter than ten years.

Our initial sample consists of 5,164 companies. To eliminate inconsistencies due to different reporting dates, we consider only firms with fiscal year-end as of December 31st. This selection criterion results in 1,208 companies leaving the sample. We also exclude companies with a negative book value (15 companies). Data availability for our main variables of interest, P, $BVPS$, and EPS, during the sample period 2005-2013 results in 2,860 companies selected. For the RRM, for which we need data also on DPS and the first lag of P, we have 2,459 companies. In Appendix A we report the composition of our sample and the mean of each variables.

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[3] The initial number of industries in the sample is 73. For two of these industries, data availability for the variables employed in the regressions results in zero observations in the regressions. Therefore, effectively we have 71 industry clusters.

[4] The two-digit SIC code is commonly employed in accounting research to identify industry clusters (see, among others, Shalev et al., 2013).

As shown in Figure 1, the sample is unbalanced, with firms exiting and entering the sample over time, causing drastic changes in market capitalization and sample size. The most dramatic change seems to be in conjunction with the financial crisis (2008-2009). We therefore have an unbalanced panel data set, and attrition bias (Hausman and Wise, 1979) may be present. We address this issue in sections 3.3 and 3.4.

[Insert Figure 1 Here]

3. Empirical examination of model specification

3.1. Choosing among OLS, RE models and FE models

We start our empirical examination by offering evidence on the importance of two tests: the Hausman test, which is employed to choose between the FE and the RE model; and the Breusch-Pagan LM test, which indicates whether a researcher should use the RE model or the OLS model.

We argue that selecting the wrong econometric model is a serious problem because it can lead to wrong inferences. For example, choosing the RE model when the FE model should be preferred (because the Hausman test is significant) may lead to wrong coefficient estimates. This bias may significantly affect the magnitude (and, potentially, sign) of the coefficients for the PRM or RRM model. On the other hand, if the Hausman test is insignificant the RE model should be chosen, and using the FE model may result in statistically insignificant coefficients even when they would be statistically significant for the RE model. Similarly, if the Breusch-Pagan LM test is significant, the RE model should be preferred. However, if the Breusch-Pagan LM test is insignificant, the pooled OLS model will be more efficient than the RE model.

In Table 1 we report the results of estimating the PRM and RRM on the whole sample, and we employ the "robust" Hausman test (Arellano, 1993, and Wooldridge, 2002, and 2010) and the Breusch-Pagan LM test to understand which model should be employed. Table 1 shows that using the RE model for the PRM leads to inconsistent coefficient estimates, because the Hausman p-value is 0.000 (see table in Table 1, Panel A). This is consistent with the large difference in the coefficients for the RE and FE models, suggesting that the RE model leads to inconsistent estimates. Conversely, using the FE model for the RRM leads to an insignificant coefficient for *ΔDEPS* (see table in Table 1, Panel B), while using the RE model results in significant coefficients for both *ΔDEPS* and *DEPS*. This is consistent with the higher efficiency for the RE estimator relative to the FE estimator. Note that, as evidenced by the Hausman p-value (0.197), the RE model should be preferred to the FE model. The Breusch-Pagan LM test results for Panel B suggest that the RE model should be preferred to the OLS model, because the P-value is less than 0.05.

[Insert Table 1 Here]

In Table 2 we provide the results of robust Hausman tests and Breusch-Pagan LM tests for country-based sub-samples. In Table 2 we denote the robust version of the Hausman test AW, the Breusch-Pagan LM test BP.[5] This table is connected with Tables 3 and 4 (reported below), and in particular specification (3), which includes firm FE, and specification (1), which considers a pooled OLS without any FE.

The results reported in Table 2 show that in 13 out of 17 cases for the PRM we reject the null hypothesis that the RE model is consistent, and we find evidence that the FE model is the most suitable method for the estimation of the PRM. For certain countries (for example, Portugal), lack of significance for the Hausman test may be due to the small number of observations, which may reduce the power of the test (Clark and Linzer, 2015). Conversely, the model with firm FE does not perform very well for the RRM: only for 9 out of 17 countries is the model with firm FE preferred to the RE model. The RE model is preferred for countries with a large number of observations (such as France), and even for the whole sample considering all 17 countries. This finding suggests that, in this case, the number of observations is unlikely to be the main cause for lack of significance of the Hausman test. Further, the results for the Breusch-Pagan LM test suggest that in six out of the nine cases (the eight cases for the individual countries and the case for the whole sample) the pooled OLS should be

[5] Using the original version of the Hausman test also results in similar rejection rates. However, the results for the two tests is inconsistent for certain countries. Therefore, choosing the robust version of the Hausman test is important.

the preferred model (in other words, the FE model and the RE model do not perform better than the pooled OLS model). Some of these cases refer to countries with a small number of observations (for example, Luxembourg or Ireland).

[Insert Table 2 Here]

3.2. Results for country-based sub-samples: coefficient estimates and statistical significance

In Tables 3 and 4 we report the results (coefficient estimates and statistical significance level) for six different specifications for the PRM and the RRM, respectively, for 17 regressions (one for each country in the sample):[6]

i) Pooled OLS with heteroskedasticity-robust standard errors, clustered on the firm level (model 1);

ii) Pooled OLS with year FE, and heteroskedasticity-robust standard errors, clustered on the firm level (model 2);

iii) FE model (where the panel unit is the firm), with heteroskedasticity-robust standard errors, clustered on the firm level (model 3);

iv) FE model (where the panel unit is the firm) with year FE, and with heteroskedasticity-robust standard errors, clustered on the firm level (model 4);

v) Pooled OLS with industry FE, and heteroskedasticity-robust standard errors, clustered on the firm level (model 5);

vi) Pooled OLS with industry and year FE, and heteroskedasticity-robust standard errors, clustered on the firm level (model 6).[7]

[6] We decide to cluster the standard errors on the firm level because the number of industries is less than 20 for six countries, and papers such as Cameron and Miller (2015), Carter et al. (2013), Kezdi (2004), and Wooldridge (2003) warn against clustering the standard errors when the number of clusters is small. In particular, Carter et al. (2013) suggest that even when the actual number of clusters is above 20 the "effective" number of clusters can be smaller once cluster heterogeneity is allowed for. This is likely to be the case in our sample, because the number of observations for each cluster is not fixed (that is, we have unbalanced clusters). For Luxembourg we have a number of firms smaller than 20: this suggests the results for Luxembourg should be read with caution because the standard errors may be biased. For this reason, we run the six regressions for Luxembourg even without clustering. The results for the regressions without clustering (untabulated but available upon request) suggest that clustering in this case generates *smaller* standard errors.

[7] None of the firms in the sample changes industry or country of origin during the sample period. For this reason, we cannot include both firm FE and industry FE or (in the analysis for the whole sample) both firm FE and country FE. We resort to testing the impact of industry FE and country FE in regressions without firm FE.

The results suggest that the type of specification chosen bears a strong impact on the magnitude and statistical significance of the coefficients of the variables, and, in some cases, even the sign of the coefficient changes. For instance, in Table 3 (PRM), we find that for several countries (Denmark, Finland, Luxembourg and Norway), when we introduce both firm FE and year FE the sign coefficient of *BVPS* changes from positive (pooled OLS case) to negative. For some countries (e.g. Germany), the introduction of firm FE and year FE causes a dramatic reduction in the size and statistical significance of the coefficient on *BVPS* (from 1.183, significant at the 1% level) to 0.108 (insignificant).

Wilcoxon and two-sample t-tests (reported at the bottom of Table 3) suggest that adding firm FE, country FE, or industry FE leads to significantly different coefficients for *EPS*, but not for *BVPS*. Adding only year FE does not lead to significantly different coefficients in comparison with the pooled OLS model. The coefficient on *BVPS* is significant at the 5% level only in eight cases out of 17 for specifications (1), (2), and (3), in nine cases for specification (4) and in ten cases for specifications (5) and (6).

The coefficient on *EPS* is significant in seven cases of out 17 for specification (5), in eight cases for specification (6), and in nine cases for specifications (1) – (4). In other words, the specification chosen affects inferences on whether *BVPS* or *EPS* bear an impact on stock price.

[Insert Table 3 Here]

Consistent with the results reported in Table 3, Table 4 highlights that there are substantial changes for the slope coefficients and related statistical significance of both of the variables of the RRM when firm FE or industry FE are included. The average coefficient on *DEPS* tends to increase as a result of the inclusion of firm FE from 0.85 to 1.83 (this difference is significant, according to both Wilcoxon tests and two-sample t-tests), while the coefficients on *ΔDEPS* tend to decrease (the mean drops from 0.34 to -0.36, and the Wilcoxon and two-sample t-tests are significant at the 1% level). The coefficient for *ΔDEPS* in the models with firm FE (and even in the model with both industry and year FE) is negative, which is counterintuitive (a positive change in earnings decreases stock returns).[8] This result is *not* due to an outlier that is pushing the average coefficient for *ΔDEPS* below zero (as said above, we winsorise all variables).[9]

When industry FE (but not year FE) are in the regressions, the results are similar to those for the model without year FE, firm FE or industry FE (pooled OLS), and also to those of the specification with only year FE. However, when both industry FE and year FE are considered, the results are similar to those with both firm FE and year FE. As for the statistical significance of the models, the results for the coefficients on *DEPS* are significant in 11 cases out of 17 for specifications (1), (3), and (4), in nine cases for specification (2), and in eight cases for specifications (5) and (6). For *ΔDEPS*, there are only six significant cases for specifications (1) and (2), and including firm FE reduces further the number of significant coefficients (four when only firm FE are included, in model (3), and two if both firm and year FE are included, in model (4)). For models (5) and (6) there are three and five significant coefficients, respectively.

[Insert Table 4 Here]

In Tables 3 and 4 we have clustered the standard errors on the firm level. Because of the importance of clustering the standard errors (Petersen, 2009), we now briefly examine the impact of running the same regressions *without* clustering. These results are untabulated but available from the authors upon request. As reported above, for Luxembourg the number of firm-clusters is relatively small and this may have led to biased standard errors (Cameron and Miller, 2015). However, when we estimate the regressions without clustering on the firm level, the results in terms of statistical significance of the coefficients on *BVPS* and *EPS* remain unaltered relative to those reported in Table 3. The results related to Table 4, instead, change in a number of cases. The number of significant

[8] The high proportion of negative coefficients for *ΔDEPS* decreases substantially when we employ Earnings Before Interest and Taxes (EBIT), instead of earnings. This suggests that the transitory earnings issue (Ota, 2003) may be causing such counterintuitive results.

[9] For the specification with only year FE, the coefficient on *ΔDEPS* is positive in 15 cases out of 17, while in the model with firm FE (and that with both firm and year FE), the coefficient is positive in only four cases out of 17, and in the remaining 13 cases it becomes negative.

coefficients on *DEPS* increases when there is no clustering for all six specifications,[10] suggesting that neglecting within-firm correlation may lead to upward biased standard errors. However, this is not the case for the coefficients on *ΔDEPS*, for which the number of significant coefficients decreases, increases, or remains the same.[11]

We now examine briefly the results reported in Tables 3 and 4 in conjunction with the results reported in Table 2. For the sake of brevity, we focus on several cases that stand out. For example, for Italy the results for the PRM coefficients are significant only when firm FE are included (specifications (3) and (4) in Table 3). The results in Table 2 for the robust version of the Hausman test confirm that firm FE matter: the p-value for Italy for the PRM is 0.006. Similarly, the results in Table 4 for Austria suggest that the coefficient on *ΔDEPS* is positive and significant when firm FE are not included (columns (1) and (2) of Table 4) and negative and insignificant when firm FE are included. The p-value for the robust version of the Hausman test is 0.002, confirming that including firm FE has a significant impact on the coefficient estimates, and the RE and OLS coefficient estimates are therefore inconsistent.

3.3 The role of different types of fixed effects and attrition

In Table 5, we report the results of OLS regressions for the PRM and RRM where year FE, country FE, and industry FE are included, while firm FE are excluded. We also report F-tests to show the incremental explanatory power of each type of FE. This is useful to examine whether a type of FE is redundant once the other types of FE are included. All types of FE are important, as the F-tests are significant at either the 1% or 5% level. This finding suggests that time-varying (but panel-invariant) variables captured by year effects, industry time-invariant variables, and country time-invariant variables are, at least to some extent, independent of each other.

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[10] The number of significant coefficients on *DEPS* increases when clustering is not performed, as follows: from 11 to 13 for specification (1), from nine to 13 for specification (2), from 11 to 12 for specifications (3) and (4), from eight to 12 for specification (5) and from eight to ten for specification (6).

[11] The number of significant coefficients on ΔDEPS increases when clustering is not performed for specifications (4) and (5), remains the same for specifications (1) and (2), and *decreases* for specifications (3) and (6).

[Insert Table 5 Here]

In Tables 6 and 7 we dig deeper into the impact of unobserved heterogeneity by comparing the results for a pooled OLS model with those of models that allow for a variety of FE: i) pooled OLS; ii) year FE; iii) firm FE; iv) both firm and year FE; v) industry FE; vi) industry and year FE; and vii) country and year FE.[12]

Finally, to examine the potential impact of attrition, we also run the regressions with firm and year FE with a balanced panel of 528 firms that are in our sample throughout the period from 2005 to 2013 (model (8)). The remaining firms come from 15 countries (we lose Luxembourg and Denmark) and 56 industries.

Consistent with the results reported above for the 17 country sub-samples (Table 3), the results reported in Table 6 demonstrate that adding firm FE reduces the coefficient on *EPS* (from around 4.5 to around 1.8) in the PRM. The coefficient on *BVPS* in the PRM also decreases (from around 0.76 to around 0.34). Industry FE, country FE and year FE bear a negligible effect on either coefficient. According to Amir et al. (2016), as the number of industries increases, the importance of industry FE should increase. However, despite the fact that we have 71 industry clusters but only 17 country clusters, industry FE are not more important than country FE. This finding suggests that heterogeneity at the industry level for European studies is not very strong. Only firm FE result in a substantial decrease in the coefficients on both *BVPS* and *EPS*, which remain statistically significant for all specifications. Firm FE also result in a substantial decrease in R-squared values. In specification (8), where we use a balanced panel of 528 firms for a model with both firm FE and year FE, the explanatory power of the model increases relative to the corresponding specification with an

[12] In untabulated results, we also look at the impact of country-level institutional factors such as: *Rule of law*, which captures the degree to which agents trust the rules of society, as well as quality of contract enforcement, property rights, police, and the courts (source: Worldwide Governance Indicators Database, www.govindicators.org); *Absence*, which proxies for the extent to which a topic is covered only by IAS/IFRS but not by domestic accounting standards and *Divergence*, which measures the extent to which rules for the same item differ between domestic accounting standards and IAS/IFRS (Nobes, 2001); *Control of Corruption*, which represents the extent to which public power is perceived to be used for private gain (source: Worldwide Governance Indicators Database, www.govindicators.org); and *Legal Origin*, which proxies for the legal origin of the company law or commercial code of each country as defined in La Porta et al. (1998). The results are very similar to those reported in Tables 6 and 7.

unbalanced panel: the R-squared increases from 21.2% to 37%.[13] This finding indicates that the association between market and book values for new firms and firms that eventually become delisted is weaker than for other firms, which in turn may indicate attrition bias, which is particularly harmful for FE models (Verbeek, 1990).

[Insert Table 6 Here]

The results in Table 7 confirm the results reported in Table 4 with respect to the impact of firm FE on the coefficients of both *DEPS* and *ΔDEPS*: firm FE result in an increase of the coefficient on *DEPS* and a decrease in the coefficient on *ΔDEPS*. Unlike in the sub-sample estimations, the coefficient on *ΔDEPS* does not become negative. Industry and country FE do not bear a significant impact on the coefficient estimates of either variable. The coefficients on *DEPS* are significant for all specifications but those on *ΔDEPS* are insignificant when firm FE are included. The inclusion of year FE is associated with a strong increase in R-squared values. This finding suggests that the RRM model is highly sensitive to macroeconomic changes that affect all firms in a certain year. Finally, the results for the FE model with year FE when we use a balanced panel of 528 firms suggest that the R-squared improves relative to that of the same regression on an unbalanced panel (from 33.7% to 41.1%). This finding is consistent with the results reported for the PRM in Table 6. The magnitude of the coefficient on *DEPS* increases. The coefficient on *ΔDEPS* remains insignificant, similar to what reported for the unbalanced panel.[14]

[Insert Table 7 Here]

3.4 Monte Carlo simulations

The results of our empirical analysis show that replacing firm FE with other types of FE may be inappropriate, consistent with the findings by Amir et al. (2016), based on Monte Carlo simulations. Amir et al. (2016), however, focus on a fixed number of periods (10). In this section, we examine the

[13] This is the "within" R-squared, based on the variation within firm clusters.

[14] In untabulated results, we have run regressions that exclude countries for which the RE model is preferred to the FE model as reported in Tables 3 and 4. The results are substantially the same as those reported in Tables 6 and 7.

impact of the length of the sample period and attrition on the bias resulting from neglecting firm FE. In particular, we provide an examination of the impact of omitting firm FE when year, country, and industry FE are included on the bias of the coefficients. We also compare the size of the standard errors of the coefficients across specifications, to evaluate the relative efficiency of the OLS, RE and FE model.

Our Monte Carlo simulations are calibrated according to the parameter values estimated in the previous section and reported in Table 5. For the sake of brevity, we focus our discussion on the PRM, but our results extend to the RRM as well.

The specifications considered are as follows: i) pooled OLS; ii) OLS with year FE; iii) OLS with year and country FE; iv) OLS with year and industry FE; v) RE model with year FE; and vi) FE model (that is, model with firm FE) with year FE.

We run 500 replications using simulated data for a sample of firms with the same composition (in terms of country and industry of origin of the firms) as that used for the empirical analysis above. This is done by replacing the data for *P*, *BVPS* and *EPS* for each firm in the dataset with simulated data. For the simulations, we keep in our dataset only firms for which we have information about the country and SIC code. The number of firms is therefore 2,842, as in Table 6, (models (5) and (6)). To understand how the length of the sample period affects the bias in the coefficients and standard errors, we run the replications considering 10 periods for Panel A and 5 periods for Panel B (that is, T = 10 in the first case, and T = 5 in the second case). Moreover, to examine the effect of attrition bias, Panel C considers a maximum number of periods equal to 10 (Max(T) = 10), but with attrition bias leading to an average time span equal to 9 periods (T-bar = 9).[15] More details on the Data Generating Process (DGP) are presented in the notes below Table 8.

In both cases (T = 10, and T = 5), the models with the firm and year FE provide the smallest bias in both the coefficients and standard errors of the coefficients. The results show that the average

[15] As explained in the notes to Table 8, we allow 20% of the firms to exit the sample from the sixth period onwards (50% of the sample period). This results in a loss of (20% * 50%) = 10% of the observations.

coefficient bias increases as T decreases when firm FE are not included. For Panel C, we find that the bias is slightly bigger than for T = 10, but smaller than for T = 5, consistent with the fact that T-bar = 9. The bias is larger for OLS models, and slightly smaller for the RE model. However, in both cases the bias is substantial. Even the bias for the standard errors is smallest for the FE model with year FE. These findings suggest that the impact of neglecting firm FE becomes bigger as T decreases, and attrition bias exacerbates this problem.

[Insert Table 8 here]

4. Conclusions and implications for future research

In this study, we have investigated whether unobserved heterogeneity is important in value-relevance research as it is in other areas of the economics and finance literature.

We have used a large panel of European listed firms to investigate the impact of firm FE, industry FE, and country FE on the coefficient estimates and corresponding *t*-statistics and p-values. While most empirical studies on value relevance focus their discussion on the estimated *t*-statistics and p-values, wrong coefficient estimates can seriously impair the validity of the economic interpretation of valuation models. For example, in the PRM, the coefficient on *EPS* represents the change in stock price following a change by one unit in *EPS*. Therefore, a biased regression coefficient can lead researchers to over- or under-estimate the importance of changes in *EPS* when assessing the value of a company. This problem is also likely to undermine the reliability of empirical studies evaluating the effects of the changes in accounting regulation on capital markets, leading to important implications for policy making. A positive and statistically significant coefficient is not enough to evaluate the impact of a regulation, because policy makers are often interested in the change in the magnitude of the coefficient. For example, an increase in the coefficient on *EPS* in the post-IFRS period may be interpreted as an indication of stronger value relevance of *EPS* (Devalle et al., 2010).

In this paper, we have offered several important contributions. First, we have uncovered important cross-country heterogeneities in the importance of firm FE for both the PRM and RRM when these models are employed separately for each of the country-based sub-samples. Industry FE, on the other hand, do not appear to bear a substantial impact on inferences, despite the fact that the number of industry dummies in our sample is rather large (71). In particular, we show that neglecting firm FE in the estimation of the PRM and RRM may lead to a substantial bias in both the size of the coefficients and the corresponding *t*-statistics of the variables of the PRM and RRM. Using Monte Carlo simulations, we have shown that the bias increases as the sample period becomes shorter, or in the presence of attrition bias.

Second, our results have demonstrated that both industry FE and country FE bear a negligible effect on the magnitude and statistical significance of the coefficients. For this reason, allowing for industry FE and country FE may not be enough to correctly estimate the impact of the variables in the PRM and RRM for studies based on European listed firms.

Finally, we examine the impact of clustering the standard errors and attrition and we find that both of them can lead to wrong inferences. Clustering the standard errors should allow for the impact of a small number of cluster on the bias of the standard error estimates. Attrition is particularly important for studies that consider the period of the financial crisis, because of the large number of firms that exit the sample during this period.

To decide whether to add or not firm FE in the estimation of the PRM and RRM in a European setting, we suggest that researchers employ "robust" Hausman tests, because the choice between RE and FE models is sample-dependent and thus which model should be preferred cannot be determined *a priori*. If the RE model is preferred, researchers should also test whether the pooled OLS model may be appropriate using the Breusch-Pagan LM test. Further, we suggest that year FE be included in the regression, unless the researcher is interested in the effect of time-varying macroeconomic components whose coefficients would be unidentified in the presence of year FE. Robustness tests considering the impact of industry and country FE and clustering the standard errors on different levels (including two-level clustering) may also be useful.

To support researchers interested in value relevance studies in Europe, we also provide a “toolbox" in Table 9, which summarises the main implications of our findings.

[Insert Table 9 Here]

Clearly, we have not assessed the influence of different estimation techniques on the PRM and RRM under all conceivable conditions. However, our findings support researchers interested in evaluating the impact of regulation on value relevance by offering guidance on how different econometric models may impinge on the estimation of the PRM and RRM.

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Table 1: Impact of using incorrectly the FE model or the RE model.

	Panel A		Panel B	
All countries	PRM RE model	PRM FE model	RRM RE model	RRM FE model
BVPS	0.635***	0.340***		
	(0.086)	(0.107)		
EPS	2.290***	1.858***		
	(0.367)	(0.331)		
DEPS			0.395***	0.723**
			(0.124)	(0.322)
ΔDEPS			0.209***	0.076
			(0.042)	(0.110)
Constant	13.064***	24.978***	0.037***	0.008
	(1.905)	(2.957)	(0.012)	(0.031)
Hausman AW	**0.000**		**0.197**	
Breusch-Pagan LM			**0.000**	
Clustering	Firm	Firm	Firm	Firm
Observations	15,656	15,656	11,424	11,424
Number of firms	2,860	2,860	2,459	2,459
R-squared (overall)	0.7617	0.7645	0.0320	0.0283

Notes: The two specifications employed are as follows:

Panel A: PRM: $P_{it} = a + bBVPS_{it} + cEPS_{it} + e_{it}$

Where P_{it} is stock price, as at six months after fiscal year-end (Lang et al., 2006; Barth et al., 2008). $BVPS_{it}$ and EPS_{it} are the book value per share, and the earnings per share, respectively. All variables are winsorised at the 1st and 99th percentile.

Panel B: RRM: $RET_{it} = a + bEPS_{it} / P_{it-1} + c\Delta EPS_{it} / P_{it-1} + e_{it}$

where $RET_{it} = \dfrac{P_{it} + DPS_{it} - P_{it-1}}{P_{it-1}}$ and $\Delta EPS_{it} = EPS_{it} - EPS_{it-1}$ (Barth and Clinch, 2009).

Hausman AW refers to the refinement of Hausman's test by Arellano (1993) and Wooldridge (2002, 2010) method, which allows for errors that are not Independent and Identically Distributed (IID). Breusch-Pagan LM denotes Breusch-Pagan LM test for the choices of either RE model or Pooled OLS.

*** p<0.01, ** p<0.05, * p<0.1.

Table 2: Results for the robust Hausman and Breusch-Pagan LM tests for PRM and RRM for 17 European countries.

	(1)	(2)	(3)	(4)
Country	**PRM AW p-value**	**PRM BP p-value**	**RRM AW p-value**	**RRM BP p-value**
Austria	0.000		0.002	
Belgium	0.063	0.000	0.009	
Denmark	0.000		0.001	
Finland	0.000		0.005	
France	0.000		0.552	0.000
Germany	0.000		0.016	
Greece	0.329	0.000	0.000	
Ireland	0.000		a)	1.000
Italy	0.006		0.000	
Lux.burg	0.048		0.127	0.403
Neth.nds	0.419	0.000	0.707	0.325
Norway	0.000		a)	1.000
Portugal	0.164	0.000	0.652	0.224
Spain	0.005		0.030	
Sweden	0.000		0.164	0.015
Switz.nd	0.000		a)	1.000
UK	0.001		0.000	
ALL	0.000		0.197	0.000

Notes: This table presents the p-values for robust Hausman tests and Breusch-Pagan tests to choose between FE models, RE models, and OLS models. PRM stands for Price Regression Model and RRM stands for Return Regression Model. For more information on these models, see notes to Table 1 and equations (1) and (2). AW refers to the refinement of Hausman's test by Arellano (1993) and Wooldridge (2002, 2010) method, which allows for errors that are not Independent and Identically Distributed (IID). BP denotes Breusch-Pagan LM test for choosing between the RE model and a Pooled OLS. [a)] The estimates for the RE model are degenerate, because the value for theta suggests that the pooled OLS model is to be preferred. Rejection of the null hypothesis for AW (p-value < 0.05 for a 5% significance level) suggests that the FE model should be preferred to the RE model. Rejection of the null hypothesis for BP (p-value < 0.05 for a 5% significance level) suggests that the RE model should be preferred to the pooled model.

Table 3: Results for the PRM regressions for 17 European countries: estimated coefficients for BVPS and EPS.

	(1)		(2)		(3)		(4)		(5)		(6)	
Country	**BVPS**	**EPS**	**BVPS**	**EPS**	**BVPS**	**EPS**	**BVPS**	**EPS**	**BVPS**	**EPS**	**BVPS**	**EPS**
Austria	0.959***	3.432	0.921***	3.839	2.376***	1.941	2.363***	1.887	0.952***	3.579	0.916***	3.973
Belgium	0.824***	3.722**	0.822***	3.761**	0.978*	1.086	0.978*	1.141	0.899***	2.978**	0.887***	3.082**
Denmark	0.602	6.178	0.608	6.097	-0.142	3.411***	-0.159	3.087***	0.794*	4.128	0.817*	3.846
Finland	0.459	5.604**	0.467	5.538**	-0.530***	5.412***	-0.496**	5.190***	0.514	5.204**	0.539	5.013**
France	0.622***	5.687***	0.622***	5.677***	0.223	1.525***	0.225	1.463***	0.626***	5.449***	0.627***	5.437***
Germany	1.183***	-0.806	1.187***	-0.830	0.119	0.872	0.108	0.842	1.099***	-0.746	1.106***	-0.783
Greece	0.431***	4.841***	0.446***	4.751***	0.452***	5.947***	0.479***	5.765***	0.388***	3.413*	0.408***	3.296*
Ireland	0.945	11.591***	0.812	12.287***	3.911***	-0.033	3.634***	0.769	1.771**	5.610*	1.519**	6.508**
Italy	0.142	2.260	0.153	2.088	1.079***	1.764***	1.106***	1.543**	0.225	1.577	0.235	1.369
Lux.burg	0.007	0.675	-0.011	0.981*	0.003	-0.021	-0.038**	0.316***	0.021	-1.972	-0.041	-0.401
Neth.nds	1.024***	2.109	1.037***	2.026	1.085***	2.462	1.164***	2.257	0.807***	2.223	0.824***	2.112
Norway	0.872***	2.658*	0.882***	2.570*	-0.165	1.252**	-0.091	1.131*	0.834***	1.261	0.846***	1.168
Portugal	0.095	3.774**	0.109	3.721**	1.125	2.062	1.222	1.746	0.255	3.772**	0.247	3.722**
Spain	0.696*	-0.004	0.705*	-0.033	0.167*	4.521***	0.162*	4.600***	0.305*	0.267	0.308*	0.254
Sweden	0.252	7.161***	0.252	7.165***	0.610***	4.210***	0.617***	4.168***	0.287*	6.727***	0.287*	6.724***
Switz.nd	0.391***	9.081***	0.385***	9.122***	0.580***	2.814***	0.516***	2.855***	0.459***	8.570***	0.455***	8.605***
UK	0.304	2.748***	0.287	2.835***	0.446*	0.635	0.419*	0.737*	0.620***	2.203***	0.602***	2.282***
Wilcoxon			**0.8313**	**0.7946**	**0.7226**	**0.0277****	**0.5862**	**0.0245****	**0.2868**	**0.0036*****	**0.2868**	**0.0049*****
Two-sample t-test			**0.4416**	**0.3436**	**0.5602**	**0.0483****	**0.5595**	**0.0384****	**0.3268**	**0.0185****	**0.3759**	**0.0160****

Notes: This table presents the coefficients for the variables of the PRM using a variety of specifications with different types of fixed effects (FE). PRM stands for Price Regression Model. For more information on this model, see notes to Table 1 and equation (1). The six specifications employed are as follows: (1) Pooled OLS, (2) Pooled OLS with year fixed-effects, (3) FE regression (firm fixed-effects), (4) FE regression with year fixed-effects, (5) OLS with industry fixed-effects, (6) OLS with both industry and year fixed effects. For all specifications, standard errors are heteroscedasticity-robust and clustered at the firm level. Wilcoxon denotes the p-value for a Wilcoxon signed-rank test (Wilcoxon, 1945) on the distributions of the coefficients for BVPS and EPS for specification (1) as compared to specifications (2) – (6). The null hypothesis is that both distributions are the same. Two- sample t-test reports the p-value for a test for equality of means of the distribution of the coefficient for specification (1) as compared to specifications (2) – (6).
*** p<0.01, ** p<0.05, * p<0.1.

Table 4: Results for the RRM regressions for 17 European countries: estimated coefficients for DEPS and ΔDEPS.

	(1)		(2)		(3)		(4)		(5)		(6)	
Country	**DEPS**	**ΔDEPS**	**DEPS**	**ΔDEPS**	**DEPS**	**ΔDEPS**	**DEPS**	**ΔDEPS**	**DEPS**	**ΔDEPS**	**DEPS**	**ΔDEPS**
Austria	1.247**	2.536***	1.170**	2.008***	6.009***	-1.306	4.346**	-0.598	1.471	1.914*	0.986	1.519
Belgium	0.560**	0.199	0.515**	0.099	1.218***	-0.341	1.224***	-0.429	0.578**	0.164	0.569**	0.027
Denmark	1.261	0.336	1.054	0.264	1.703	-0.660	1.713	-0.717	1.190	0.313	1.024	0.237
Finland	0.080	0.157	0.132	0.080	0.243	-0.081	0.448*	-0.215	0.155	0.061	0.199	-0.010
France	0.396	0.28***	0.375*	0.215**	0.357	0.276***	0.346	0.198***	0.396	0.270***	0.376*	0.207**
Germany	0.471***	0.294***	0.426***	0.285***	1.192***	-0.090	1.129***	-0.087	0.454**	0.295***	0.404***	0.288***
Greece	1.693***	0.904***	0.945***	0.931***	3.231***	0.119	2.030***	0.302	1.964***	0.776**	1.112***	0.831***
Ireland	1.250**	-0.042	0.903*	0.195	2.471	-1.236	1.991**	-1.015	1.794*	-0.557	1.361*	-0.311
Italy	0.730***	0.421**	0.401**	0.562***	2.098***	-0.531**	1.194***	-0.070	1.043***	0.260	0.657***	0.439***
Lux.burg	0.197**	0.011	0.225*	-0.029	0.377***	-0.075**	0.347***	-0.048	-1.252	7.257	a)	a)
Neth.nds	0.513	-0.026	0.436	0.032	0.595	0.024	0.586	0.059	0.605	0.038	0.485	0.083
Norway	0.026	0.546**	-0.307	0.630***	1.535***	-0.299	0.374	0.217	0.340	0.283	-0.085	0.470**
Portugal	0.842*	0.085	0.731**	-0.002	0.409	0.195	1.059*	-0.189	0.145	0.253	0.326	0.099
Spain	0.240**	0.126	0.210*	0.075	0.821***	-0.092	0.687**	-0.094	0.263***	0.123	0.219**	0.081
Sweden	0.563***	0.032	0.413**	0.050	1.319**	-0.057	1.046**	-0.005	0.542**	0.039	0.409**	0.061
Switz.nd	3.654***	-0.299	2.701***	0.061	5.627***	-1.626***	4.001***	-0.969**	3.781***	-0.357	2.790***	0.022
UK	0.739***	0.148	0.739***	0.142	1.889***	-0.312*	1.772***	-0.306*	0.842***	0.063	0.842***	0.055
Wilcoxon			**0.0019*** **	**0.7583**	**0.0008*** **	**0.0010*** **	**0.0004*** **	**0.0006*** **	**0.1359**	**0.1024**	**0.0340** **	**0.0879* **
Two-sample t-test			**0.0090*** **	**0.8861**	**0.0033** **	**0.0071*** **	**0.0036*** **	**0.0055*** **	**0.9369**	**0.4694**	**0.0329** **	**0.1704**

Notes: This table presents the coefficients for the variables of the RRM using a variety of specifications with different types of fixed effects (FE). RRM stands for Return Regression Model. For more information on this model, see notes to Table 1 and equation (2). DEPS is earnings per share (EPS) divided by the first lag of stock price and ΔDEPS is the first difference in EPS divided by the first lag of stock price. The six specifications employed are as follows: (1) Pooled OLS, (2) Pooled OLS with year fixed-effects, (3) FE regression (firm fixed-effects), (4) FE regression with year fixed-effects, (5) OLS with industry fixed-effects, (6) OLS with both industry and year fixed effects. For all specifications, standard errors are heteroscedasticity-robust and clustered at the firm level. [a)] For this specification, the number of observations is insufficient to estimate the regression parameters. Wilcoxon denotes the p-value for a Wilcoxon signed-rank test (Wilcoxon, 1945) on the distributions of the coefficients for DEPS and ΔDEPS for specification (1) as compared to specifications (2) – (6). The null hypothesis is that both distributions are the same. Two- sample t-test reports the p-value for a test for equality of means of the distribution of the coefficient for specification (1) as compared to specifications (2) – (6).*** p<0.01, ** p<0.05, * p<0.1.

Table 5: OLS regressions where year FE, country FE, and industry FE are included, while firm FE are excluded.

	(1) PRM	(2) RRM
BVPS	0.730***	
	(72.249)	
EPS	4.306***	
	(44.220)	
DEPS		0.327***
		(14.965)
ΔDEPS		0.188***
		(8.028)
Year, Country, and Industry FE	YES	YES
Firm FE	NO	NO
F-test for joint significance of Year FE	10.14***	626.59***
F-test for joint significance of Country FE	41.17***	4.21***
F-test for joint significance of Industry FE	7.13***	1.39**
Observations	15,656	11,424
Firms	2,860	2,459
R-squared	0.782	0.312

Notes: This table presents the results of a cross-country analysis using the PRM and RRM models where year FE, country FE, and industry FE are included, while firm FE are excluded. PRM stands for Price Regression Model and RRM stands for Return Regression Model. For more information on these models, see notes to Table 1 and equations (1) and (2). In Column (1), PRM is estimated while Column (2) reports the estimates for the RRM model Constant included in all specifications but not reported.

Table 6: Results for the whole sample using different types of fixed effects: PRM.

PRM	(1) OLS no FE	(2) OLS year FE	(3) OLS firm FE	(4) OLS firm and year FE	(5) OLS industry FE	(6) OLS ind. & year FE	(7) OLS Country and year FE	(8) OLS (balanced panel) firm and year FE
BVPS	0.756***	0.757***	0.340***	0.335***	0.741***	0.742***	0.741***	0.568***
	(7.447)	(7.433)	(3.161)	(3.077)	(7.356)	(7.342)	(7.476)	(3.982)
EPS	4.585***	4.574***	1.858***	1.842***	4.638***	4.627***	4.315***	2.372***
	(4.431)	(4.408)	(5.614)	(5.573)	(4.507)	(4.483)	(4.372)	(3.841)
Observations	15,656	15,656	15,656	15,656	15,610	15,610	15,656	4,752
R-squared	0.765	0.766	0.181	0.212	0.769	0.770	0.774	0.370
Industry FE	NO	NO	NO	NO	YES	YES	NO	NO
Year FE	NO	YES	NO	YES	NO	YES	YES	YES
Country FE	NO	NO	NO	NO	NO	NO	YES	NO
Firm FE	NO	NO	YES	YES	NO	NO	NO	YES
Number of countries	17	17	17	17	17	17	17	15
Number of industries	71	71	71	71	71	71	71	56
Number of firms	2,860	2,860	2,860	2,860	2,842	2,842	2,860	528

Notes: This table presents the results of a cross-country analysis using the PRM model. PRM stands for Price Regression. For more information on this model, see notes to Table 1 and equation (1). In Column (1), PRM is estimated using Pooled OLS. Column (2) estimates the PRM model using Pooled OLS with year effects, Column (3) is estimated PRM model with firm fixed-effects, Column (4) uses FE regression with year fixed-effects to estimate PRM model, Column (5) uses OLS with industry fixed-effects for PRM model, Column (6) uses OLS with both industry and year fixed effects and Column (7) uses OLS with country and year fixed effects. For all specifications, standard errors are heteroscedasticity-robust and clustered at the firm level. Constant included in all specifications but not reported.

Table 7: Results for the whole sample using different types of fixed effects: RRM.

RRM	(1) OLS no FE	(2) OLS year FE	(3) OLS firm FE	(4) OLS firm and year FE	(5) OLS industry FE	(6) OLS ind. & year FE	(7) OLS Country and year FE	(8) OLS (balanced panel) firm and year FE
DEPS	0.354***	0.315***	0.723**	0.645**	0.361***	0.320***	0.325***	1.233***
	(3.174)	(3.239)	(2.247)	(2.432)	(3.103)	(3.166)	(3.364)	(3.026)
ΔDEPS	0.230***	0.196***	0.076	0.051	0.229***	0.195***	0.193***	-0.105
	(5.180)	(4.868)	(0.692)	(0.578)	(5.088)	(4.798)	(4.831)	(-0.549)
Observations	11,424	11,424	11,424	11,424	11,401	11,401	11,424	4,224
R-squared	0.032	0.302	0.040	0.337	0.039	0.308	0.306	0.411
Industry FE	NO	NO	NO	NO	YES	YES	NO	NO
Year FE	NO	YES	NO	YES	NO	YES	YES	YES
Country FE	NO	NO	NO	NO	NO	NO	YES	NO
Firm FE	NO	NO	YES	YES	NO	NO	NO	YES
Number of countries	17	17	17	17	17	17	17	15
Number of industries	71	71	71	71	71	71	71	56
Number of firms	2,459	2,459	2,459	2,459	2,450	2,450	2,459	528

Notes: This table presents the results of a cross-country analysis using the RRM model. RRM stands for Return Regression Model. For more information on this model, see notes to Table 1 and equation (2). In Column (1), RRM is estimated using Pooled OLS. Column (2) estimates the RRM model using Pooled OLS with year effects, Column (3) is estimated RRM model with firm fixed-effects, Column (4) uses FE regression with year fixed-effects to estimate RRM model, Column (5) uses OLS with industry fixed-effects for RRM model, Column (6) uses OLS with both industry and year fixed effects and Column (7) uses OLS interacted industry and year fixed effects. For all specifications, standard errors are heteroscedasticity-robust and clustered at the firm level. Constant included in all specifications but not reported.

Table 8: Monte Carlo simulations: Impact of sample period length on the bias resulting from neglecting firm FE.

		(1)	(2)	(3)	(4)	(5)	(6)
	PRM Variable	PRM Coefficient bias	PRM Standard errors bias	PRM Coefficient bias	PRM Standard errors bias	PRM Coefficient bias	PRM Standard errors bias
		Panel A T = 10		**Panel B T = 5**		**Panel C Max(T) = 10**	**Attrition bias T-bar = 9**
OLS without any FE	BVPS	0.08293	0.00054	0.13873	0.00101	0.08168	0.00046
	EPS	0.08258	0.00053	0.13829	0.00080	0.08228	0.00044
OLS with year FE	BVPS	0.08296	0.00054	0.13876	0.00101	0.08171	0.00045
	EPS	0.08261	0.00053	0.13832	0.00080	0.08229	0.00044
OLS with year and country FE	BVPS	0.08265	0.00054	0.13865	0.00101	0.08149	0.00045
	EPS	0.08229	0.00053	0.13814	0.00079	0.08207	0.00044
OLS with year and industry FE	BVPS	0.08099	0.00054	0.13705	0.00101	0.07992	0.00045
	EPS	0.08063	0.00053	0.13659	0.00080	0.08051	0.00044
RE model with year FE	BVPS	0.06531	0.00054	0.11536	0.00099	0.06413	0.00045
	EPS	0.06493	0.00052	0.11492	0.00078	0.06465	0.00043
FE model with year FE	**BVPS**	**0.00031**	**0.00021**	**0.00081**	**0.00004**	**-0.00008**	**0.00006**
	EPS	**-0.00017**	**0.00019**	**0.00042**	**0.00026**	**0.00024**	**0.00004**

Notes: In this Table we report the results of 500 Monte Carlo simulations for the coefficient bias and standard error bias resulting from neglecting firm FE when they are correlated with explanatory variables of the PRM: BVPS and EPS. Panel A considers 10 fictitious periods (T = 10), Panel B five periods (T = 5), and Panel C considers maximum number of periods equal to 10, but we attrition bias leading to an average time span equal to 9 periods.

In Columns denoted with (1), (3), and (5) we report the coefficient bias, that is, the average difference between the coefficient value used to simulate the DGP (see equation below) and the estimated coefficient for each of the 500 simulations. In Columns (2), (4), and (6) we report average difference (in absolute value) between the estimated standard errors and the true standard errors, calculated following Petersen (2009). To ensure that the simulations are comparable to our sample in terms number of firms in each industry and country, we consider all the firms in our dataset that have a SIC number (2,842), but we replace the actual data on *P*, *BVPS* and *EPS* with simulated data. In particular, we employ the following Data Generating Processes (DGP):

$$P_{it} = 0.730BVPS_{it} + 4.306EPS_{it} + c_i + s_i + \eta_i + y_t + u_{it}$$

Where c_i stand for the country-level factors (time invariant), s_i are industry-level factors (time invariant), η_i are firm-level factors,[16] y_t are time-varying factors (the same for all fictitious firms), and u_{it} is a standard normal variable with mean zero and variance one. $BVPS_{it}$ and EPS_{it} are simulated as normal variables. To ensure that macroeconomic shocks at the country level are independent of industry-level shocks, and firm-specific shocks are independent of both country-level and industry-level shocks (formally, $c_i \perp s_i \perp \eta_i$) we assign randomly each firm to a country and industry. We simulate these shocks so that the distribution of each shock is normal. For Panel C, we allow 20% of the firms to exit the sample from the sixth period onwards (50% of the sample period). This results in a loss of 20% * 50% = 10% of the observations, and an average sample period equal to 9 periods (that is, 10 – 0.1*10).

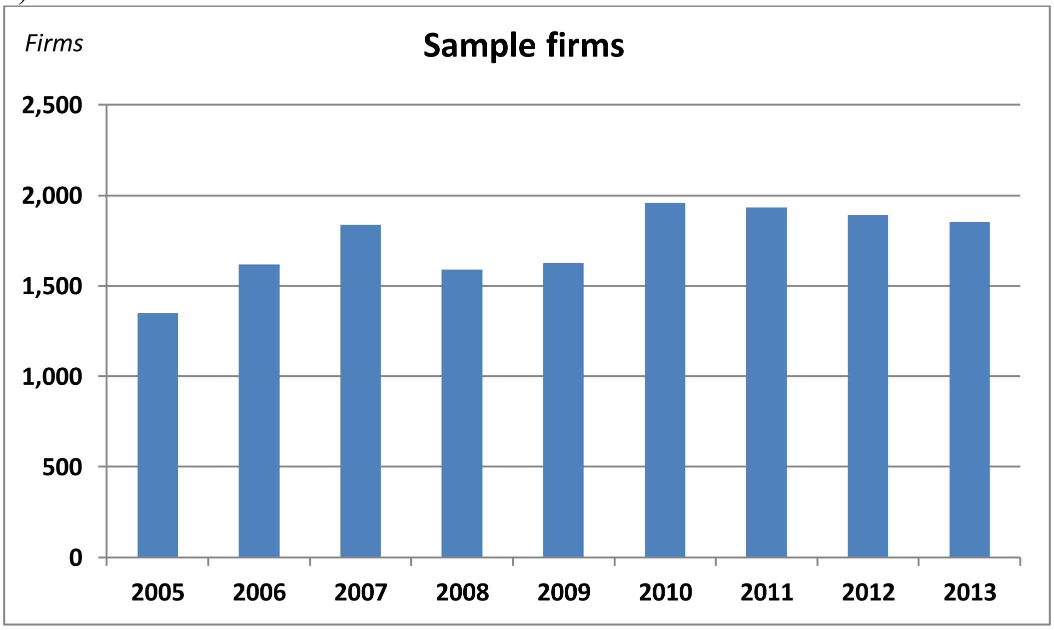
[16] These could be interpreted as different types of macro- (that is, industry or country level) and micro-economic shocks.

Table 9: Tips for applied researchers.

Econometric Issue	Suggested approach
How to choose among FE model, RE model, and OLS model	*Run the robust version of the Hausman test:* *1. If significant, use FE model;* *2. If insignificant, Breusch-Pagan LM test:* *a. If significant, use RE model;* b. *If insignificant, use OLS model.* *In cross-country studies, we suggest that the researchers compare the results for the whole sample with those for country-based sub-sample. For countries with a small number of firms, the results of the tests should be considered with caution.* **Note:** *In some cases, a researcher may decide that it is appropriate to include firm FE (regardless of the result of robust Hausman tests) because:* *1. There is little time-series variation in explanatory variables. For example, this may happen if the PRM or RRM models are augmented with corporate governance variables.* *2. The researcher believes that accounting data is uncorrelated with time-invariant unobserved factors. However, in this case, we suggest that the researcher clarifies the reasons for her assumption and briefly discusses the robust Hausman test results.*
How to deal with year FE, industry FE and country FE	*Industry FE and country FE cannot replace firm FE.* *Year FE are needed unless time-varying macroeconomic components that are the same for each firm are included (e.g., GDP for single-country study).* **Note:** *Depending on the research questions, robustness tests considering the impact of industry and country FE may also be useful. In certain cases, the researcher may want to examine time-invariant factors that are not necessarily unique to the individual.*
Clustering	*Clustering at the firm level is generally needed as standard errors are more conservative.* *When number of clusters is small, this can lead to biased standard errors – consider alternative level of clustering (for example, firm level, instead of country level).* *Robustness checks considering the impact of clustering the standard errors on different levels (including two-level clustering) may be helpful.*
Attrition bias	*Allow for potential attrition bias, especially for FE models.* *Studies with a sample period that includes the financial crisis, which can lead to a sudden drop in the number of sample firms, should consider the impact of attrition on coefficient estimates as well as R-squared values.*

Figure 1. Number of sample firms and total market capitalisation for the whole sample (in millions of Euros) during 2005-2013.

a)



b)

Appendix A. *Sample composition.*

2-digit SIC	Obs.ns	2-digit SIC	Obs.ns	2-digit SIC	Obs.ns	2-digit SIC	Obs.ns	Country	Obs.ns	Firms	SIC	P	BVPS	EPS	RET	DEPS	ΔDEPS
												Mean					
01	17	28	472	48	275	72	63	AUSTRIA	117	37	12	68.684	52.424	5.061	0.169	0.105	0.002
02	43	29	56	49	365	73	1.522	BELGIUM	626	107	28	64.629	49.745	4.809	0.046	0.095	-0.004
07	0	30	145	50	529	75	29	DENMARK	224	71	19	70.271	82.024	8.274	0.193	0.098	0.004
09	11	32	199	51	269	76	9	FINLAND	652	100	31	12.758	8.019	1.225	0.043	0.086	0.001
10	41	33	133	52	23	78	58	FRANCE	3.010	513	50	96.221	78.071	6.377	0.094	0.125	-0.025
12	16	34	130	53	18	79	91	GERMANY	2.821	509	49	62.343	77.647	7.920	0.109	0.118	0.001
13	145	35	511	54	13	80	74	GREECE	821	169	42	5.555	4.908	0.518	0.078	0.098	-0.010
14	54	36	391	55	4	81	0	IRELAND	137	28	17	10.734	4.118	0.608	0.158	0.099	0.006
15	402	37	201	56	49	82	17	ITALY	935	178	43	9.070	7.520	0.705	0.059	0.088	-0.006
16	61	38	176	57	22	83	12	LUXEMBOURG	53	18	7	28.956	44.245	4.944	0.114	0.326	0.023
17	108	39	58	58	59	84	16	NETHERLANDS	596	104	28	101.626	43.950	8.284	0.090	0.097	-0.001
20	449	40	9	59	68	87	766	NORWAY	473	92	29	12.669	9.744	1.234	0.040	0.113	0.004
21	18	41	49	60	128	91	5	PORTUGAL	213	40	10	5.318	4.166	0.541	0.057	0.108	-0.003
22	73	42	33	61	765	94	2	SPAIN	640	124	29	20.164	16.471	3.405	0.031	0.195	0.001
23	55	43	18	62	42	96	8	SWEDEN	1.261	232	29	11.670	6.806	1.211	0.120	0.102	-0.001
24	36	44	206	64	64	97	9	SWITZERLAND	888	139	14	482.551	236.072	28.754	0.113	0.073	0.003
25	58	45	81	65	655			U.K.	2.189	399	56	5.019	2.856	0.463	0.147	0.104	-0.004
26	116	46	9	67	4.475	**Total**	**15,610**	Total	**15.656**	**2.860**	**71**	**69.552**	**50.816**	**5.436**	**0.098**	**0.111**	**0.006**
27	365	47	72	70	89												

Notes: SIC is the two-digit Standard Industry Classification code. Mean is the sample average for each of the variables.